Background

- Progress of medical imaging devices
  -- Segmentation, detection, functional analysis
  -- Image-information based surgery

Diagnostic and Therapeutic Assistance

- Patient anatomy understanding
  -- Organ segmentation
  -- Anatomical labeling
- Pre-operative simulation
  -- 3D interactive rendering
  -- Organ deformation
- Intra-operative assistance
  -- Surgical navigation
  -- Decision support
- Post-operative assistance
  -- Follow-up diagnosis

Abdominal Organs

- Liver
- Spleen
- Pancreas
- Kidneys
- Small intestine
- Large Intestines
- Arteries
- Veins
- ...

Computational Anatomy

- Whole body understanding by computer
- Medical Image Understanding
  - Segmentation
    - Atlas-based segmentation
  - Anatomical labeling
    - Common language in medical communication
  - ...
- Application to diagnostic and therapeutic aid
  - Laparoscopic surgery

Muti-organ segmentation

- Segmentation of abdominal organs from CT datasets
- Atlas-based segmentation is widely used in this area
  - Similar to brain segmentation
  - Required to consider large variances of abdominal organ locations and shapes
  - Patient-specific atlas would achieve better segmentation accuracy.

Atlas

- A set of CT volumes and thei corresponding manual segmentations

Multi-organ abdominal CT segmentation using hierarchically weighted subject-specific atlases

Robin Wolz, Chengwen Chu, Kazunari Misawa, Kensaku Mori and Daniel Rueckert

Biomedical Image Analysis Group, Imperial College London
Department of Media Science, Nagoya University
Aichi Cancer Center, Nagoya

Wolz et al. TMI 2013

Motivation

- Segmenting abdominal organs on CT scans is a crucial step in many clinical applications, e.g.
  - Computer aided diagnosis (CAD)
  - Computer assisted laparoscopic surgery
- Automated segmentation enables fast and accurate processing of large amounts

Motivation

- Abdominal organs display a large variability in terms of the position and shape of different organs
- Previous methods are often customized to a particular organ, e.g.
  - Liver segmentation with multi-organ atlases [Ocada 2010]
  - Multi-stage model for pancreas segmentation [Shimizu 2010]
Overview

- Underlying idea: Use atlas-based segmentation
- Combines techniques from
  - multi-atlas registration [Rohlfing 2004; Heckemann 2006]
  - patch-based segmentation [Coupé 2011; Rousseau 2011]
- Approach specifically addresses challenges in abdominal imaging
  - Robust to inter-subject variation and field of view
  - Applicable to multiple organs without specialisation
- Proposed method is
  - generic and not customized to any particular organ
  - builds subject-specific atlas directly from available atlases

Method

- A multi-level approach is used to define a target-specific atlas for all organs of interest
- This generates a specific model for the unseen image by using the most suitable cases in the atlas database
  - weighted at all levels
- A probabilistic atlas is obtained by combining weights at all levels
- A final segmentation is sought from the probabilistic atlas

\[
l(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} w_i w_j l(x_{ij})
\]

\[
\Delta(R,n) = \sum_{j \in R} \left[ l(x_j) - A_{i,j} \right]^{\frac{1}{2}}
\]

Results

- Results using CT scans from 150 subjects
- Graph-cuts based refinement is used for hard segmentation

<table>
<thead>
<tr>
<th>Structure</th>
<th>Dice</th>
<th>Jaccard</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kidneys</td>
<td>90.3</td>
<td>86.4</td>
</tr>
<tr>
<td>Liver</td>
<td>94.1</td>
<td>93.5</td>
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<tr>
<td>Pancreas</td>
<td>88.2</td>
<td>85.8</td>
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<tr>
<td>Spleen</td>
<td>90.0</td>
<td>87.7</td>
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</tbody>
</table>

- An increased accuracy can be observed at every level of locality
- More variable structures benefit more from the localised measure

Construction of local probabilistic atlas based on relationship between organ location and its application to pancreas segmentation

Chengwen Chu, Yuichiro Hayashi, Yukitaka Nimura, Masahiro Oda, Kazunari Misawa, Takayuki Kitasaka, Daniel Rueckert, and Kensaku Mori

Pancreas segmentation

- Challenge in pancreas segmentation
  - Large inter-patient variances in both pancreatic shape and position
- Statistical models computed from multi-atlases
  - Global Probabilistic atlases (PAs) are utilized for whole abdominal region [1][2]
Problem of previous approach

- Low segmentation accuracy for pancreas segmentation
- Quality of PAs is affected by large inter-subject differences of pancreas
  - Large inter-subject differences in pancreas shape and position
- Existence probability diffusion in pancreas atlas not suitable for segmentation

Probabilistic atlas considering pancreas location

- Generate local pancreas-specific PA
- Use spatial relationship in atlas selection
- Aim to reduce influence of large inter-patient differences in both pancreas position and shape

Atlas-based segmentation considering positional relationships of organs

- Reduce influence of inter-subject differences in pancreas position
  - Use "spatial relationship" between liver and pancreas
  - Extract local "interest region of pancreas" from global CT volumes
- Reduce influence of inter-subject difference in pancreas shape
  - Select "most similar atlases" for target image based on atlas-target similarity
  - Target image: unlabeled image needed to be segmented

Step 1 Estimate pancreas existence region

- Calculate the center of the gravity of pre-segmented liver region
- Calculate the center of the gravity of unknown pancreas region
  - Use calculated center of gravity of liver
  - Use pre-computed average liver-pancreas distance
- Obtain cubic volume of interest from original CT volume
  - VOI is located at estimated pancreas center and has (2R) mm edge

Pancreas VOI computation

![Pancreas VOI computation diagram]

Fig.1 Estimation of pancreas existence region

Step 2 Select atlases similar to target volume

- Register all the atlases to target image using MRF-based method [3]
  - Registration is performed on volume of interest of pancreas (Pancreas VOI)
- Calculate atlas-target similarities: Normalized cross correlation is used
- Select most similar N atlases for each target image
Step 3 Generate patient-specific and pancreas-specific PA

\[ \Lambda_p(l) = \sum_{i=1}^{N} \omega(i) \delta(L_p^i, l) / \sum_{i=1}^{N} \omega(i) \]

\[ \delta(l, l') = \begin{cases} 1 & \text{if } l = l' \\ 0 & \text{otherwise} \end{cases} \]

\( p \) : Voxel in image space \( i \) : Index of atlas
\( N \) : Number of selected atlas \( L_p^i \) : Label image of atlas
\( \omega(i) \) : Similarity between atlas \( i \) and target image
\( l \) : Label of background or pancreas: 0, 1

Step 4 Pancreas region segmentation

- Coarse segmentation is done by Maximum a posterior (MAP) segmentation

\[ P(l | I_p) \propto [P(I_p | l) \cdot P(l)] \]

Intensity distribution \( P(l) \)
Probabilistic atlas

- Refine coarse segmentation by graph-cut

Experiments

- 100 portal-phased abdominal CT volumes
- Size of existence region of pancreas
  - 301 × 301 × 301 mm³
- Number of atlases to be selected are changed as 1, 5, 10, 15, 20, 40, 60, 80 and 99

<table>
<thead>
<tr>
<th>Image Size</th>
<th>512 × 512 x (238 – 538) voxels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel spacing</td>
<td>0.546 – 0.820 mm</td>
</tr>
<tr>
<td>Slice thickness</td>
<td>0.400 – 0.800 mm</td>
</tr>
<tr>
<td>Reconstruction pitch</td>
<td>0.400 – 0.800 mm</td>
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</tbody>
</table>

Segmentation Results

<table>
<thead>
<tr>
<th>( N )</th>
<th>JI (%)</th>
<th>Std (%)</th>
<th>Dice (%)</th>
<th>Std (%)</th>
<th>ASD (mm)</th>
<th>Std (mm)</th>
<th>( N = 1 )</th>
<th>( N = 5 )</th>
<th>( N = 10 )</th>
<th>( N = 15 )</th>
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<tbody>
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</tbody>
</table>

Results

Excellent

Good

Poor

JI=84.8%

Best segmentation result with corresponding PA used in pancreas segmentation.
Segmentation results are outlined in yellow with ground-truth in red on an axial slice.
Results

Worst segmentation result with corresponding PA used in pancreas segmentation. Segmentation results are outlined in yellow with ground-truth in red on an axial slice.

Intensity information to anatomical information

Anatomical Structure Understanding

Computational Meta Anatomy

Textual Information for Anatomical Structure Representation

Automated anatomical labeling of abdominal arteries extracted from CT images based on machine learning

Kensaku Mori¹, Bui Hui Hoang¹, Tetsuro Matsuzaki¹, Masahiro Oda¹, Takayuki Kitasaka, Michitaka Fujiwara, Kazunari Misawa
¹Nagoya University, ²Aichi Institute of Technology, ³Aichi Cancer Center

Anatomical Names

- Anatomical names
  - Very important information to understand and recognize patient anatomy
  - Utilized for describing patient anatomy
  - “Common language” in medical communication

Laparoscopic Surgery and Image-Guided Surgical Planning

- Planning stage
  - Observe abdominal vasculature by using three-dimensional rendering obtained from CT (i.e. volume rendering)
  - Determine surgical strategy based on information obtained from the rendered images

- Vasculature understanding
  - Important surgical process for achieving safer surgery because anatomy differs among patients

- Automated display anatomical name
  - Would be helpful to understand anatomy

Problem Formulation of Anatomical Labeling of blood vessels

- Input
  - Tree structure \( B = \{ b_i \} \)
    - \( i = 1, \ldots, N \): The number of branches
    - \( b_i \): \( i \)-th branch in the tree structure

- Output
  - Category Set \( C = \{ c_i \} \)
    - \( c_i \): Anatomical names assigned to branch \( i \)

Process overview

- Learning of branching variations of arteries
  - Multiclass AdaBoost technique
    - Using six features of artery branches
      - Running direction, curvature, thickness etc.

- Global optimization by rule of majority
  - Correction by taking neighbors’ names into account

Labeling target

- Abdominal aorta (Ao)
- Celiac artery (CA)
- Right renal artery (RRA)
- Left renal artery (LRA)
- Common hepatic artery (CHA)
- Splenic artery (SA)
- Superior mesenteric artery (SMA)
- Inferior mesenteric artery (IMA)
- Right and left internal iliac arteries (RIIA+LIIA)
- Right and left common iliac arteries (RCIA+LCIA)
- Right and left external iliac arteries (REIA+LEIA)

Examples of features

- Diameter: \( T_i \)
- Average curvature: \( \frac{1}{N} \sum_{i=1}^{N} m_i \)
- Unit vector connecting the starting and the ending voxel
- Vectors from \( O_2 \) to starting voxel of branch \( i \)
- Vectors from the branching point on the Ao to the target branch
Experimental results

<table>
<thead>
<tr>
<th>Artery</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>Recall rate(%)</th>
<th>Precision rate(%)</th>
<th>F-value(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ao</td>
<td>300</td>
<td>2</td>
<td>3</td>
<td>99.3</td>
<td>99.0</td>
<td>99.2</td>
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<tr>
<td>CA*</td>
<td>47</td>
<td>4</td>
<td>14</td>
<td>92.2</td>
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<td>83.9</td>
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<tr>
<td>CHA*</td>
<td>20</td>
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<td>13</td>
<td>66.7</td>
<td>60.6</td>
<td>63.5</td>
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<td>SA*</td>
<td>34</td>
<td>8</td>
<td>10</td>
<td>81.0</td>
<td>77.3</td>
<td>79.1</td>
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<tr>
<td>RRA*</td>
<td>32</td>
<td>1</td>
<td>15</td>
<td>97.0</td>
<td>68.1</td>
<td>80.0</td>
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<tr>
<td>LRA*</td>
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<td>12</td>
<td>23</td>
<td>70.0</td>
<td>54.9</td>
<td>61.5</td>
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<td>135</td>
<td>14</td>
<td>29</td>
<td>90.6</td>
<td>82.3</td>
<td>86.3</td>
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<td>IMA*</td>
<td>29</td>
<td>4</td>
<td>18</td>
<td>87.9</td>
<td>61.7</td>
<td>72.5</td>
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<tr>
<td>RIIA+LIA*</td>
<td>83</td>
<td>5</td>
<td>26</td>
<td>94.3</td>
<td>76.1</td>
<td>84.3</td>
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<tr>
<td>RCA+LIA</td>
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<td>3</td>
<td>32</td>
<td>96.2</td>
<td>70.4</td>
<td>81.3</td>
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<td>RELIA+LEIA</td>
<td>181</td>
<td>61</td>
<td>3</td>
<td>74.8</td>
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<td>Average</td>
<td>965</td>
<td>124</td>
<td>186</td>
<td>88.6</td>
<td>83.8</td>
<td>86.2</td>
</tr>
</tbody>
</table>

* Branches recognized by machine learning

Labeling results

Discussion

- Anatomical labeling of upper and lower abdominal arteries
  - Based on machine learning
  - Showed possibility of anatomical labeling by using 20-dimensional features
- Adjustment of training samples (“unknown” branches)
  - Caused increase of TP (293→393*) with increase FP (72→337*)
  - FP reduction by global optimization process (337→131*)

* Branches recognized by machine learning

Anatomical Name Drawing on Anatomical Structures for Volume Rendering

- Anatomical structure recognition
- Anatomical name rendering by two-pass rendering
  - Anatomical name drawing by using surface rendering
  - Anatomical structure drawing by using volume rendering

Anatomical Name Annotation in Volume Rendering

Jiang et al. CMIG 2013
Virtual pneumoperitoneum using MSD models

- **Real pneumoperitoneum (RP)**
  - Abdominal wall lifting by inducing gas
- **Virtual pneumoperitoneum (VP)**
  - Useful for FuCADS system
  - Introducing mass-spring-damper and motion of equations

\[
m \ddot{x} = f(x)
\]

(All forces are balanced.)
Laparoscopic surgery navigation using FuCADS

- Laparoscopic surgery navigation
  - 6 operations by February 28, 2013
  - 35 and more operations only for reference image generation
    - (Some operations are cancelled due to patients’ conditions)

Conclusions

- Computational Anatomy for diagnostic and therapeutic assistance
  - Patient anatomy understanding
  - Pre-operative simulation
  - Intra-operative assistance

- Meta Anatomy
  - Combination with textual information

- Information-augmented surgery
  - Medical image understanding based on computation anatomy